



Auxiliary diagnosis method for lead–acid battery health based on sample entropy

Yu-Hua Sun^a, Hurng-Liahng Jou^{a,*}, Jinn-Chang Wu^b

^a Department of Electrical Engineering, National Kaohsiung University of Applied Sciences, 415 Chien-Kung Road, Kaohsiung 80782, Taiwan

^b Department of Microelectronic Engineering, National Kaohsiung Marine University, Taiwan

ARTICLE INFO

Article history:

Received 14 March 2008

Received in revised form 13 October 2008

Accepted 16 May 2009

Available online 16 June 2009

Keywords:

Lead–acid battery

State-of-health

Sample Entropy

ABSTRACT

In this paper, a health auxiliary diagnosis method based on Sample Entropy (SampEn) is proposed for the lead–acid battery unit. The concept of the proposed method is that the discharging curve for a health battery unit is smooth; however, the degradation of battery unit caused by the internal shorts, opening of internal short or cell undergoing reversal will distort the discharging curve. Since SampEn can quantify the regularity of a data sequence, it can serve as an indicator for the state-of-health (SOH) of the lead–acid battery. The salient feature of the proposed method is that SOH of the battery is estimated automatically at the end of each discharging cycle by measuring the battery voltage and current of a battery unit, so that no complicated measurement is required. To verify the proposed health auxiliary diagnosis method based on SampEn, aging experiments on lead–acid battery are developed. The experimental data shows that the proposed health auxiliary diagnosis method provides the expected results.

© 2009 Elsevier Ltd. All rights reserved.

1. Introduction

Lead–acid batteries have been widely used in electric vehicles [1], stand-alone renewable power generation, back-up power supplies for communication or computer related equipment [2] and uninterruptible power supply (UPS) [3]. Although, the state of charge [4,5] and reserve life [6] of the lead–acid battery was widely used to determine the status of the battery but the health condition of lead–acid battery will evidently affect the reliability of critical loads. State-of-health (SOH) of the battery is used to supply the degradation information of battery to the users. SOH indicates the ability of the battery to perform well during charging and discharging period. If SOH can be estimated accurately, the users will know the health status of the battery and whether the battery should be replaced or not. The battery degradation may be caused by drying out, grid corrosion, thermal runaway, electrolyte leakage, internal shorts [7,8], opening of internal short or cell undergoing reversal [9]. Several methods have already been developed to estimate the SOH of a battery [10]. These methods can be categorized into three types:

- (a) Capacity: capacity is the most popular method to indicate the SOH [11]. In this type, the life of a battery is defined to stop when its capacity is decreased to about 80% of the initial capacity for general battery [12] and 60% of the initial capacity for small capacity battery [13]. SOH diagnosis by

using the capacity is the ratio between the nominal capacity of the present time to the initial time, and it is represented as [14]:

$$\text{SOH} = \frac{(\text{nominal capacity at present time})}{(\text{nominal capacity at initial time})} \quad (1)$$

- (b) Coup de fouet: the “coup de fouet” is a phenomenon specific to lead–acid battery, which occurs at the beginning of the discharging period [15]. This method involves measuring the trough voltage (low voltage point) in the “coup de fouet” region and uses it to determine the SOH of a battery [16].
- (c) Impedance techniques: impedance techniques are based on the principle that the impedance and the resistance of a valve regulated lead–acid (VRLA) battery increase as the battery ages and losing its capacity. Many impedance meters have been claimed to measure the SOH of batteries [17]. The methods of combined impedance measurements and fuzzy logic data analysis are used to estimate the SOH of the battery [18,19]. Besides the above methods, SOH diagnosis methods based on measuring the battery voltage, temperature, capacity or internal impedance have been developed [20,21] to estimate the SOH of a battery.

The capacity based SOH diagnosis method has the problems of accumulated error under small discharging current caused by integral calculation and its calculated capacity depending on the discharging current. In the Coup de fouet based SOH diagnosis method, the relation between the Coup de fouet voltage and the SOH of a battery is hard to be evaluated. In the impedance based

* Corresponding author. Tel.: +886 7 3814526x5519; fax: +886 7 3921073.
E-mail addresses: hjyou@mail.ee.kuas.edu.tw (H.-L. Jou), jinnwu@mail.nkmu.edu.tw (J.-C. Wu).

SOH diagnosis method, measuring the impedance of a battery accurately is very difficult because the impedance of battery is very small. Hence, the development of the SOH diagnosis method for a lead–acid battery is still very important for the applications of battery. Among the causes of battery degradation, the internal shorts, opening of internal short or cell undergoing reversal will result in endangering the applications of battery. Hence, detecting the degradation of battery caused by the internal shorts, opening of internal short or cell undergoing reversal is important and worth to be developed.

In science, the term “entropy” is generally interpreted in three distinct, but semi-related, ways, i.e., from macroscopic viewpoint (classical thermodynamics), a microscopic viewpoint (statistical thermodynamics), and an information viewpoint (information theory) [22]. Therefore, the entropy theorem was generally applied to thermodynamic [23], wind energy [24], heat exchanger [25], Physiological time-series analysis [26], heart rate variability [27] and so on. However, SampEn (Sample Entropy) method was never used to predict the state-of-health of the battery.

Approximate Entropy (ApEn), as defined in Pincus (1991), was used to quantify serial irregularity [28]. In addition to eliminating self-matches, the SampEn algorithm is simpler than the ApEn algorithm, requiring approximately one-half as much time to calculate.

$$\begin{array}{c}
 x(j) \rightarrow x(1) \quad x(2) \quad \dots \quad x(N-m) \quad x(N-m+1) \\
 \begin{array}{c}
 x(1) \\
 x(2) \\
 \dots \\
 x(i) \\
 \dots \\
 x(N-m) \\
 x(N-m+1)
 \end{array}
 \left[\begin{array}{cccccc}
 d(1,1) & d(1,2) & \dots & \dots & \dots & \dots \\
 d(2,2) & d(2,2) & \dots & \dots & \dots & \dots \\
 \dots & \dots & \dots & \dots & \dots & \dots \\
 \dots & \dots & \dots & \dots & \dots & \dots \\
 d(N-m,1) & d(N-m,2) & \dots & \dots & \dots & \dots \\
 d(N-m+1,1) & d(N-m+1,2) & \dots & \dots & \dots & \dots
 \end{array} \right]
 \end{array}
 \quad
 \begin{array}{cc}
 x(N-m) & x(N-m+1) \\
 \begin{array}{c}
 d(1,N-m) \\
 d(2,N-m) \\
 \dots \\
 \dots \\
 d(N-m,N-m) \\
 d(N-m+1,N-m)
 \end{array}
 &
 \begin{array}{c}
 d(1,N-m+1) \\
 d(2,N-m+1) \\
 \dots \\
 \dots \\
 d(N-m,N-m+1) \\
 d(N-m+1,N-m+1)
 \end{array}
 \end{array}$$

In comparison with ApEn, SampEn is largely independent of record length and displays relative consistency [26].

In this paper, detecting the degradation of lead–acid battery unit caused by the internal shorts, opening of internal short or cell undergoing reversal is addressed, and a novel health auxiliary diagnosis method based on Sample Entropy (SampEn) is proposed. The salient feature of the proposed method is that the SOH of the battery is estimated automatically at the end of each discharging cycle by only measuring the battery voltage and current, and it does not involve any complicated measurement procedures and avoids the accumulated error caused by integral calculation. Aging experiments of lead–acid battery are developed to verify the proposed auxiliary SOH diagnosis method.

2. Sample Entropy and health auxiliary diagnosis method

Approximate Entropy (ApEn) was developed for measuring a complex system [28]. SampEn(m, r, N) is precisely the negative natural logarithm of the conditional probability that two sequences similar for m points remain similar at the next point, where self-matches are not included in calculating the probability. Thus a lower value of SampEn also indicates more self-similarity in the time series [26]. SampEn was developed in the recent years due to it has a better representation of the entropy in the analyzed signal as comparing with ApEn [27]. For a data sequence $x(n) = x(1), x(2), x(3), \dots, x(N)$, where N is the total number of data points to calculate SampEn(r, m, N), a run length m and a tolerance window r must be specified to compute SampEn(r, m, N). In order to use fewer data points to measure the change in a complex system, the parameter m used in this paper is 2 [28]. Normally, tolerance

window, r , is 0.2 times the standard deviation (SD) of the original data [28]. SD can be represented as:

$$SD = \sqrt{\frac{1}{N-1} \sum_{n=1}^N \left[x(n) - \frac{1}{N} \sum_{n=1}^N x(n) \right]^2} \quad (2)$$

SampEn algorithm [29] can be summarized as follows:

- (1) Form m -vectors, $X(1)$ to $X(N-m+1)$ defined by:

$$X(i) = [x(i), x(i+1), \dots, x(i+m-1)] \quad i = 1 \text{ to } N-m+1 \quad (3)$$

$$X(j) = [x(j), x(j+1), \dots, x(j+m-1)] \quad j = 1 \text{ to } N-m+1 \quad (4)$$

- (2) Defining the distance $d[X(i), X(j)]$ between vectors $X(i)$ and $X(j)$ as the maximum absolute difference between their respective scalar components:

$$d[X(i), X(j)] = \max_k |x(i+k) - x(j+k)| \quad k = 0 \text{ to } m-1 \quad (5)$$

The relation matrix is show as:

- (3) Defining for each i , for $i = 1$ to $N-m+1$, let

$$B_i^m(i) = \frac{1}{N-m+1} * V^m(i) \quad (6)$$

where $V^m(i) = \text{no. of } d_m[X(i), X(j)] \leq r, i \neq j$

- (4) Similarly, defining for each i , for $i = 1$ to $N-m+1$, let

$$A_i^m(i) = \frac{1}{N-m+1} * V^{m+1}(i) \quad (7)$$

where $V^{m+1}(i) = \text{no. of } d_{m+1}[X(i), X(j)] \leq r, i \neq j$

- (5) Define

$$B^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} B_i^m(r) \quad (8)$$

$$A^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} A_i^m(r) \quad (9)$$

- (6) SampEn value for a finite data length of N can be estimated:

$$\text{SampEn}(r, m, N) = -\ln(A^m(r)/B^m(r)) \quad (10)$$

The discharging voltage will be decreased smoothly and the value of SampEn will be approached to zero for a healthy battery. The degraded battery may result in internal shorts [7,8], opening of internal short or cell undergoing reversal [9]. When a cell is shorted or undergoes reversal, it will result in an abrupt voltage

drop of a battery unit [8]. If an internally shorted cell is opened, it will result in an abrupt voltage rise of a battery unit. Hence, the degradation of battery caused by internal shorts, opening of internal short or undergoing cell reversal will distort the discharging curve of a battery unit. At the same time, the relative value of SampEn will also be changed. The proposed method is based on the concept that the above battery degradation phenomena will result in an abrupt change in the discharging voltage and SampEn. However, the battery current variation caused by the abrupt change of load will also result in abrupt change of discharging voltage. To avoid the un-corrected diagnosis caused by the abrupt change of discharging voltage, the development of a diagnosis method which can neglect the curves of discharging voltage distortion caused by the abrupt change of normal discharging current is necessary. The proposed method cannot diagnose the degraded battery phenom-

ena, such as dry out or grid corrosion, and it is only an auxiliary diagnosis method for the SOH of the battery (ADSOH).

Fig. 1 shows the flowchart of the proposed SOH diagnosis method for a battery unit. Normally, measuring devices are employed to measure and retrieve the data of voltages and currents for a battery. During the charging and discharging period, SampEn of voltage and current will be calculated. In order to avoid the effect of normal discharging current variation in determining the battery health status, the SampEn of voltage and current was compared, so that the SOH of battery can be diagnosed correctly. This means that the proposed SOH diagnosis method can avoid the effect of normal discharging current variation although the voltage may be dropped or raised abruptly due to the sudden variation of normal discharging current.

If the degradation of a battery unit is caused by internal shorts, opening of internal short or cell undergoing reversal, the battery voltage will vary immediately. At the same time, the value of ADSOH will be fluctuated evidently; so that the value of ADSOH can be converted into a SOH index to indicate the health status of battery.

3. Experimental system

The accelerated battery aging experiments developed to evaluate the charging and discharging characteristics of the lead-acid

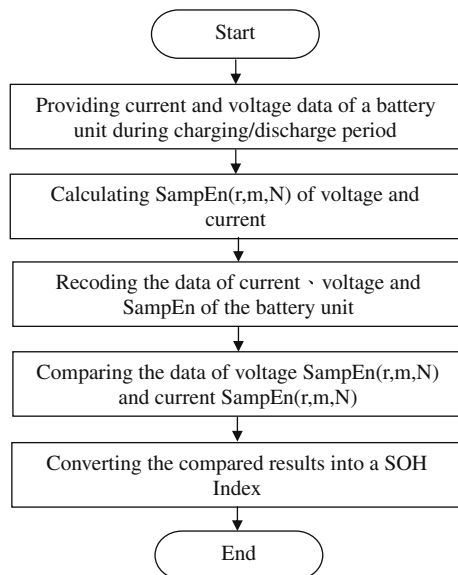


Fig. 1. Flow chart of the proposed SOH diagnosis method for a battery unit.

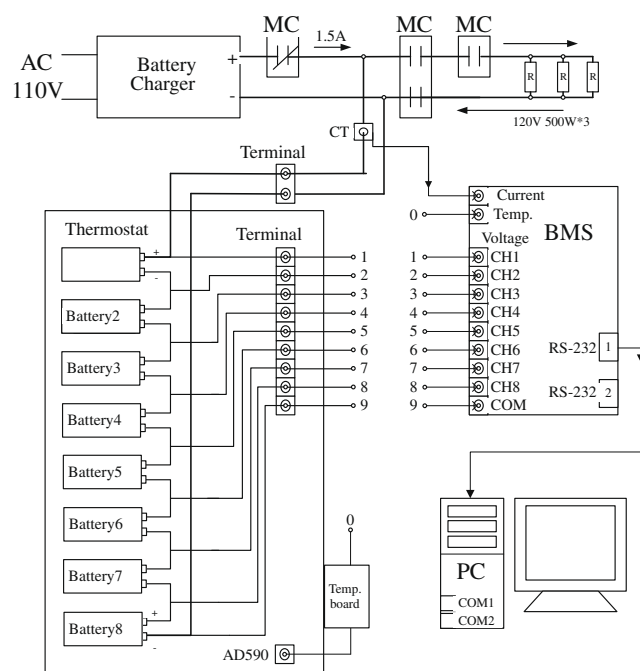


Fig. 2. Experimental system for a string of batteries.

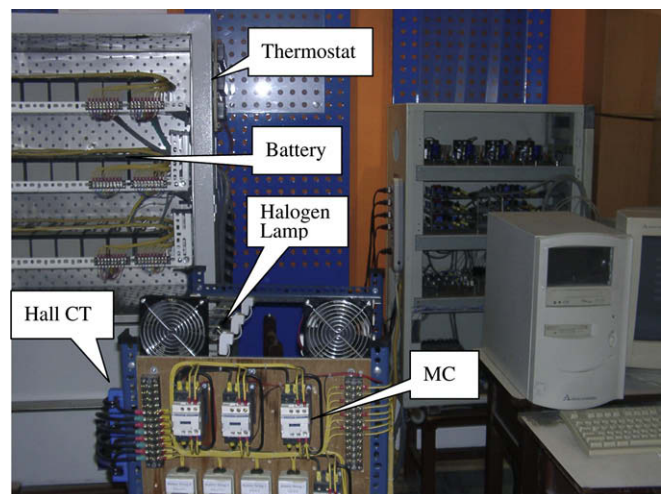


Fig. 3. Picture of experimental system.

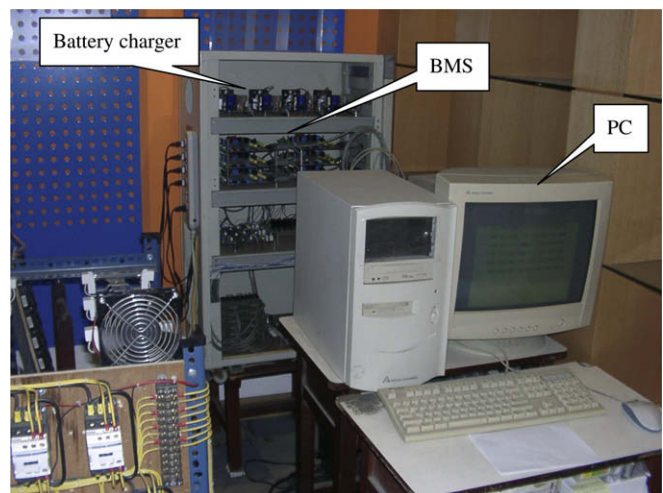


Fig. 4. Picture of experimental system.

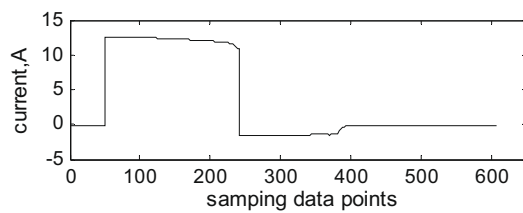
battery [30] are used to verify the proposed auxiliary SOH diagnosis method. Fig. 2 shows the experimental system. The experimental system includes a battery charger, a thermostat, several electromagnetic contactor (MC) switches, and a battery monitoring system (BMS). BMS was supported by the ABLEREX Electronics Corporation, Ltd. Each BMS card include eight input battery voltage (allowable voltage range 0–16 V) channels, one input current channel and one input temperature channel. A Hall CT is used as the transducer of input current. The accuracy of measurement will be affected by the resolution of A/D converter used in BMS. Figs. 3 and 4 show the photographs of experiment system.

The conditions for accelerated battery aging experiments are defined as follows:

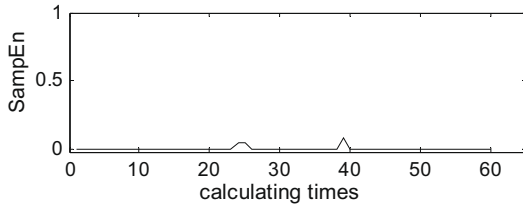
- (1) Four independent strings of batteries are used in the experiments, and each string of batteries consisted of eight 7-Ah

12-V VRLA battery units connected in series. Each battery unit consists of six cells connected in series internally.

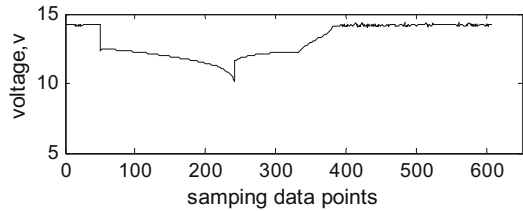
- (2) The ambient temperature was kept at 50 °C.
- (3) Sample data per 10 s was retrieved upon discharging the battery.
- (4) Sample data was retrieved every 5 min when the battery was charged.
- (5) The final discharging voltage for each string of batteries was 76.8 V.
- (6) The discharging load for each battery set was a Halogen Lamp (120 V, 500 W * 3).
- (7) The experiment stops as the capacity of each string of batteries was decreased to 60% of the initial capacity.



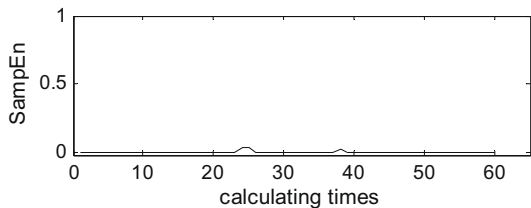
(a)



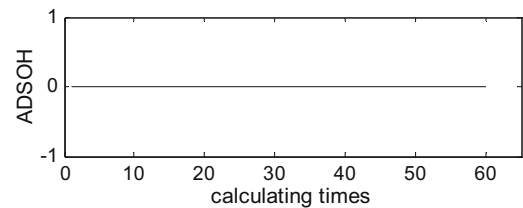
(b)



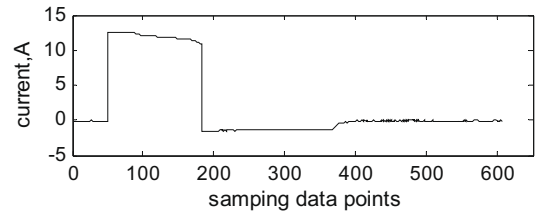
(c)



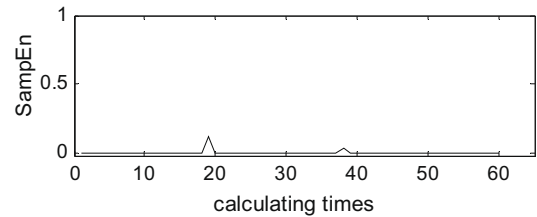
(d)



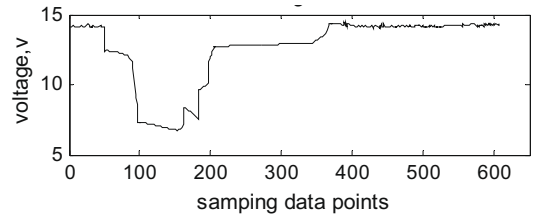
(e)



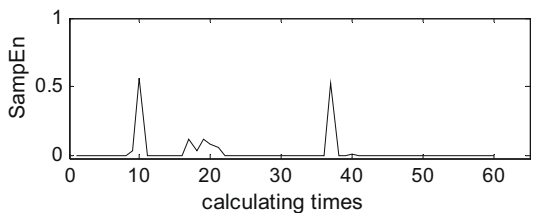
(a)



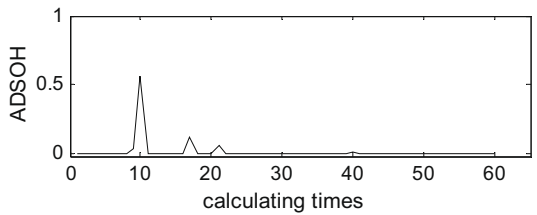
(b)



(c)



(d)



(e)

Fig. 5. Experimental results of the battery (string 1, No. 3) at 5th charging/discharging cycle, (a) charging/discharging current, (b) SampEn value of current, (c) charging/discharging voltage, (d) SampEn value of voltage, and (e) ADSOH.

Fig. 6. Experimental results of the battery (string 1, No. 3) at 159th charging/discharging cycle, (a) charging/discharging current, (b) SampEn value of current, (c) charging/discharging voltage, (d) SampEn value of voltage, and (e) ADSOH.

The experimental procedure is defined as follows:

- (1) The battery experiment was defined as the cycle use.
- (2) The output voltage of battery charger in the experiment was set 116.8 V ($14.6 \text{ V} \times 8$). Each string of battery was charged about 23 h in each cycle. The battery string is discharged after the battery was charged 23 h.
- (3) When electromagnetic contactor (MC) was energized, battery charger will be disconnected from the battery string and Halogen Lamp (120 V , $500 \text{ W} \times 3$) will connect to the sting of the battery.
- (4) The electromagnetic contactor (MC) will be de-energized when the battery voltage of each string was 76.8 V. And then, the next cycle will repeat.

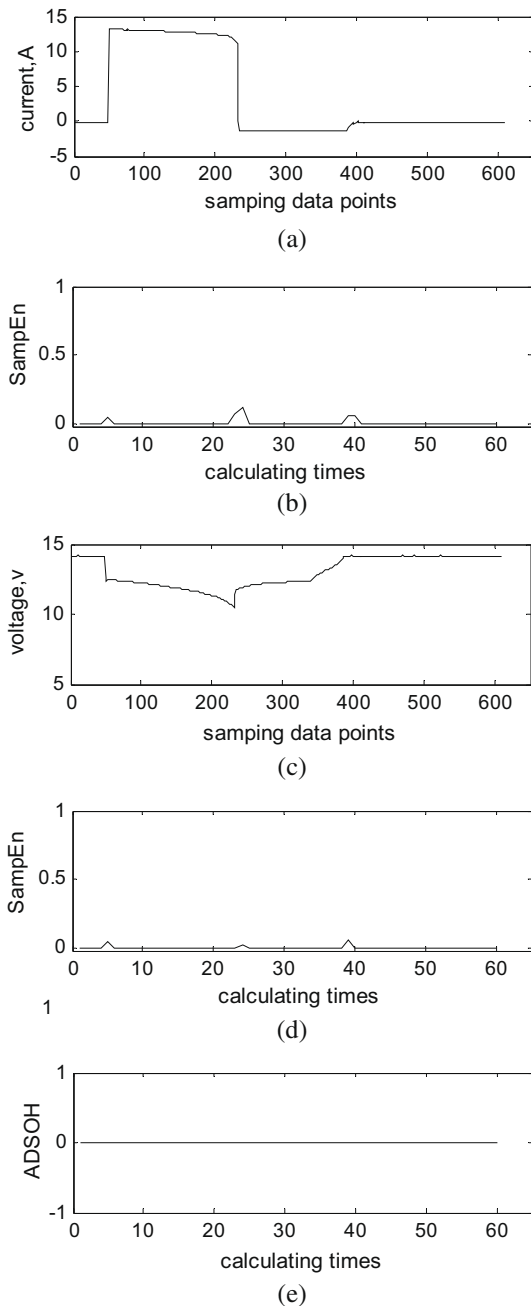


Fig. 7. Experimental results of the battery (string 2, No. 1) at 5th charging/discharging cycle, (a) charging/discharging current, (b) SampEn value of current, (c) charging/discharging voltage, (d) SampEn value of voltage, and (e) ADSOH.

4. Experimental results

Considering the charging/discharging characteristics of the battery, the value of SampEn will become divergent if the tolerance window, r , is too small. The tolerance window, r , used in the following experiments is 0.3. The total measured experimental data points of the battery (string 1, No. 3) at the 5th charging/discharging cycle is 607 points. A huge computing resource will be used for calculating SampEn if the parameter N is large, and the calculated result may be inaccurate if the parameter N is small [31]. The parameter N used in the following experiments is 10. Hence, the parameters r , m and N of SampEn used in the following experiments are 0.3, 2 and 10, respectively.

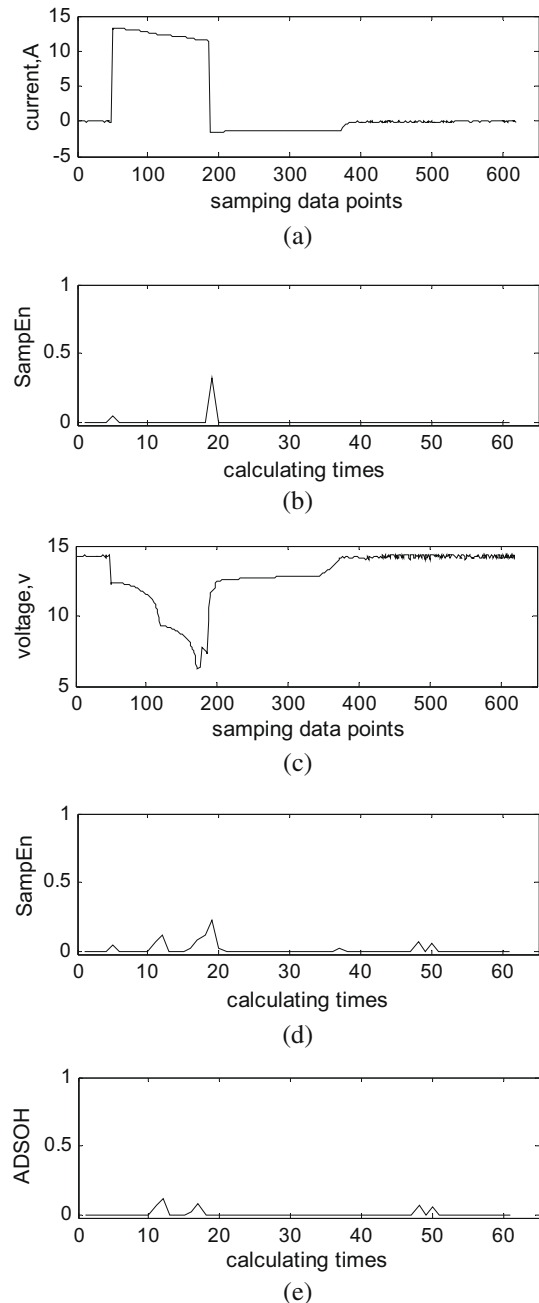


Fig. 8. Experimental results of the battery voltage (string 2, No. 1) at 107th charging/discharging cycle, (a) charging/discharging current, (b) SampEn value of current, (c) charging/discharging voltage, (d) SampEn value of voltage, and (e) ADSOH.

Fig. 5 shows the curves for the battery current and the battery voltage (string 1, No. 3) and their calculated SampEn ($r = 0.3$, $m = 2$, $N = 10$) at the 5th charging/discharging cycle. The operation modes for the battery charger include the constant current mode and the constant voltage mode, to charge the batteries, and the load used for discharging is a constant resistor. Consequently, the curves of current and voltage are smooth except when the battery is changed from charging status to discharging status, and from discharging status to charging status and from constant current charging to constant voltage charging. The calculated SampEn is nearly zero except at the points under the transition of charging/discharging status and different charging modes. If the value of current SampEn in Fig. 5b is larger than the set value (0.01 is defined), the value of voltage SampEn in Fig. 5d should be checked

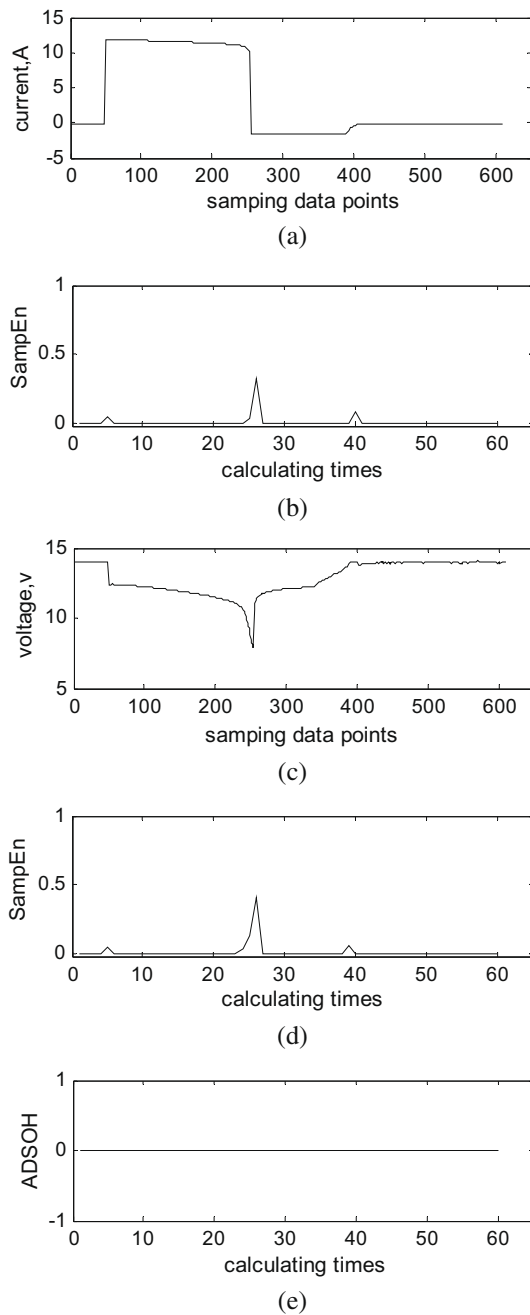


Fig. 9. Experimental results of the battery (string 3, No. 4) at 5th charging/discharging cycle, (a) charging/discharging current, (b) SampEn value of current, (c) charging/discharging voltage, (d) SampEn value of voltage, and (e) ADSOH.

at the same time. If both values of current SampEn and voltage SampEn are larger than the setting values, the value of ADSOH is defined as zero. This means that the battery is “healthy”. If only the value of voltage SampEn is larger than the setting value, the value of ADSOH will be defined to be equal to the value of voltage SampEn. This means that the battery is “degrading”. As seen in Fig. 5e, the value of ADSOH is zero and the SOH of the battery can be determined “healthy”, and there is no need to change the battery.

Fig. 6 shows the current and voltage curves of battery in string 1, No. 3 and their calculated SampEn ($r = 0.3$, $m = 2$, $N = 10$) at the 159th charging/discharging cycle. As seen in Fig. 6(a), the current curve is smooth except when the battery is changed from charging status to discharging status, from discharging status to charging

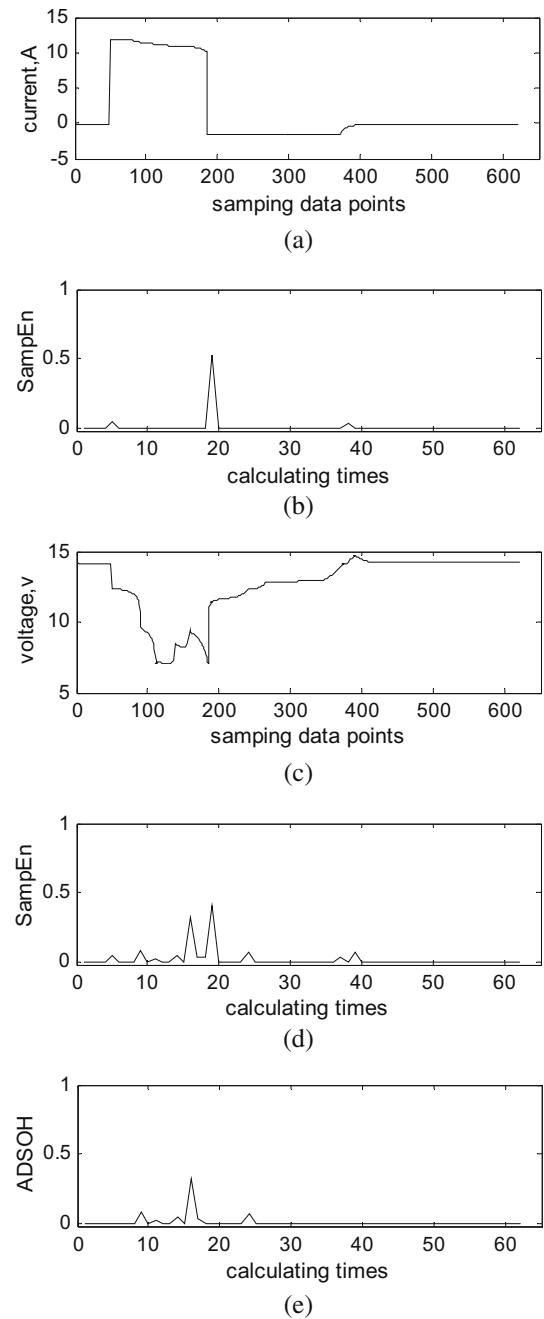


Fig. 10. Experimental results of the battery (string 3, No. 4) at 145th charging/discharging cycle, (a) charging/discharging current, (b) SampEn value of current, (c) charging/discharging voltage, (d) SmpEn value of voltage, and (e) ADSOH.

ing status and from constant current charging to constant voltage charging. As seen in Fig. 6c, the voltage curve is still abnormal when the battery is changed from charging status to discharging status, from discharging status to charging status and from constant current mode to constant voltage mode. Besides, some additional unexpected variations distort the curve seriously during the discharging status. The abrupt drop of battery voltage close to the 91 and 98 sampling data points can be explained based on the fact that some cells in the battery are shorted, and the abrupt rise of battery voltage close to the 152 sampling data point can be explained based on the fact that a shorted cell in the battery is opened. Comparing SampEn in Fig. 6b with Fig. 6d, the ADSOH results are shown in Fig. 6e. The ADSOH curve shows serious fluctuations, indicating degradation in the SOH of the battery.

Figs. 7 and 8 show the current, voltage, calculated SampEn ($r = 0.3$, $m = 2$, $N = 10$) and ADSOH curves of the battery in No. 1 of string 2, and Figs. 9 and 10 show the current, voltage, calculated SampEn ($r = 0.3$, $m = 2$, $N = 10$) and ADSOH curves of the battery in No. 4 of string 3. As seen in these figures, the curves of these two batteries are similar to the curves of battery in No. 3 of string 1. Hence, the proposed auxiliary diagnosis method based on SampEn for SOH can diagnose effectively the degradation of battery unit caused by the internal shorts, opening of internal short and the cell undergoing reversal in the discharging process.

From the above, it can conclude that the ADSOH data can be used to determine the SOH of the battery and can avoid the un-corrected diagnosis caused by abrupt change in the discharging current.

5. Conclusions

This paper proposes a novel auxiliary diagnosis method based on SampEn for SOH of a lead–acid battery unit. In this method, ADSOH is used to diagnose and indicate the degradation of the lead–acid battery unit. The salient feature of the proposed method is that the SOH of a battery is estimated automatically at the end of each discharging cycle by measuring the battery voltage and current and it does not require any complicated measurement technique. From the experimental results, the proposed SampEn based auxiliary diagnosis method can detect the degradation of battery unit caused by the internal shorts, opening of internal short or cell undergoing reversal by only detecting discharge voltage and current. Because the degradation of battery unit caused by the internal shorts, opening of internal short or cell undergoing reversal will result in endangering immediately, detecting these causes of degradation for a battery unit is important for the battery diagnosis in the practical battery applications.

References

- [1] Shen WX, Chan CC, Lo EWC, Chau KT. A new battery available capacity indicator for electric vehicles using neural network. *Energy Convers Manage* 2002;43(6):817–26.
- [2] Many S, Tokunaga M, Oda N, Hatanaka T, Tsubota M. Development of long-life small-capacity VRLA battery without dry-out failure in telecommunication application under high temperature environment. In: IEEE INTELEC; September 2000. p. 42–5.
- [3] Pascoe PE, Anbuky AH. A VRLA battery simulation model. *Energy Convers Manage* 2004;45(7–8):1015–1041.
- [4] Vasebi A, Bathae SMT, Partovibakhsh M. Predicting state of charge of lead–acid batteries for hybrid electric vehicles by extended Kalman filter. *Energy Convers Manage* 2008;49(1):75–82.
- [5] Shen WX. State of available capacity estimation for lead–acid batteries in electric vehicles using neural network. *Energy Convers Manage* 2007;48(2):433–42.
- [6] Pascoe PE, Anbuky AH. A unified discharge voltage characteristic for VRLA battery capacity and reserve time estimation. *Energy Convers Manage* 2004;44(2):277–302.
- [7] Davis E, Funk D, Johnson W. Internal Ohmic measurements and their relationship to battery capacity – EPRI's ongoing technology evolution. In: Battcon, 2002. p. 12–10.
- [8] Landwehrle Robert E. In the final analysis: post mortem tests and measurements on a VRLA battery. In: Battcon; 2005. p. 19–16.
- [9] Garche J, Jossen A, Doring H. The influence of different operating conditions, especially over-discharge, on the lifetime and performance of lead/acid batteries for photovoltaic systems. *J Power Sources* 1997;67(1–2):201–12.
- [10] Sun YH, Jou HL, Wu JC. Novel auxiliary diagnosis method for state-of-health of lead–acid battery. In: International conference on power electronics and drive systems; November 2007. p. 262–6.
- [11] Pascoe PE, Anbuky AH. Standby VRLA battery reserve life estimation. In: IEEE INTELEC; September 2004. p. 516–23.
- [12] IEEE Std. 1188–2005. IEEE recommended practices for maintenance, testing and replacement of valve regulated lead acid (VRLA) batteries in stationary applications; February 2006.
- [13] William E, Rob E, Barry R. Testing of gel-electrolyte batteries for wheelchairs. *J Rehabil Res Dev* 1988;25(2):27–32.
- [14] Okoshi Tetsuro, Yamadaa Keizo, Hirasawa Tokiyoshi, Emori Akihiko. Battery condition monitoring (BCM) technologies about lead–acid batteries. *J Power Sources* 2006;158(2):874–8.
- [15] Bose CSC, Laman FC. Battery state of health estimation through Coup De Fouet. In: IEEE INTELEC; September 2000. p. 597–601.
- [16] Delaille A, Perrin M, Huet F, Hernout L. Coup de fouet of lead–acid cells as a function of their state-of-charge and state-of-health. *J Power Sources* 2006;158(2):1019–28.
- [17] Waters AR, Bullock KR, Bose CSC. Study of the monitoring the state of health of VRLA batteries through ohmic measurements. In: IEEE INTELEC; October 1997. p. 675–80.
- [18] Singh P, Reisner D. Fuzzy logic-based state-of-health determination of lead acid batteries. In: IEEE INTELEC; October 2002. p. 583–90.
- [19] Singh P, Kaneria S, Broadhead J, Wang X, Burdick J. Fuzzy logic estimation of SOH of 125Ah VRLA batteries. In: IEEE INTELEC; September 2004. p. 524–31.
- [20] Anbuky AH, Pascoe PE, Hunter PM. Knowledge based VRLA battery monitoring and health assessment. In: IEEE INTELEC; September 2000. p. 687–94.
- [21] Takahashi K, Watakabe Y. Development of SOH monitoring system for industrial VRLA battery string. In: IEEE INTELEC; October 2003. p. 664–70.
- [22] From Wikipedia, the free encyclopedia, In: <http://en.wikipedia.org/wiki/Entropy#Definitions_and_descriptions>.
- [23] Ko TH. Thermodynamic analysis of optimal mass flow rate for fully developed laminar forced convection in a helical coiled tube based on minimal entropy generation principle. *Energy Convers Manage* 2006;47(18–19):3094–104.
- [24] Ramirez A P, Carta JA. The use of wind probability distributions derived from the maximum entropy principle in the analysis of wind energy. A case study. *Energy Convers Manage* 2006;47(15–16):2577–654.
- [25] Balkan F. Application of EoEP principle with variable heat transfer coefficient in minimizing entropy production in heat exchangers. *Energy Convers Manage* 2005;46(13–14):2134–44.
- [26] Richman JS, Moorman JR. Physiological time series analysis using approximate and sample entropy. *Am J Physiol* 2000;278(6):H2039–49.
- [27] Volkan Tuzcu, Selman Nas. Sample entropy analysis of heart rhythm following cardiac transplantation. In: IEEE international conference on systems, man and cybernetics Waikoloa; October 2005. p. 198–202.
- [28] Pincus SM. Approximate entropy as a measure of system complexity. *Proc Natl Acad Sci USA* 1991;88(6):2297–301.
- [29] Xinnian Chen, Solomon Irene C, Chon Ki H. Comparison of the use of approximate entropy and sample entropy: applications to neural respiratory signal. In: IEEE engineering in medicine and biology 27th annual conference; September 2005. p. 4212–5.
- [30] Pascoe PE, Anbuky AH. Automated battery test system. *Measurement* 2003;34(4):325–45.
- [31] Ren-Hung Wang. Application of approximate entropy for detection of electric power signals with FPGA realization. Master dissertation, Department of Electrical Engineering, National Cheng Kung University, Taiwan; 2007.